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Maria Nieswand • Matthias Walter

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DIW Berlin
German Institute for Economic Research
Mohrenstr. 58
10117 Berlin

Tel. +49 (30) 897 89-0
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Cost Efficiency and Subsidization in German Local Public Bus Transit

Maria Nieswand[a]

Matthias Walter[b]

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Abstract

Subsidies are considered important means to facilitate the provision of public transit, yet the empirical evidence implies that they can have harming effects on costs and possibly also on operators' performance. This paper examines the impacts of deficit-balancing subsidies on the cost inefficiency of local public bus companies in Germany, where a complex system allocates ample financial support. Our empirical analysis relies on a unique dataset of 33 companies observed over a period of up to twelve years for a total of 231 observations. We employ a stochastic frontier cost function for panel data that account for unobserved heterogeneity and provide firm-specific, time-varying inefficiency estimates. Further, we allow variations in the optimal technology by randomizing some cost functions' coefficients in one of our model specifications. Subsidies directly enter the inefficiency function as a heteroscedastic variable. We find a positive effect of subsidies on the standard deviation of inefficiency, which implies that the range of companies' inefficiency increases with the level of subsidies relative to total costs. However, we also find that non-subsidized firms perform better in terms of cost efficiency.

JEL Codes: C13, D24, L92

Keywords: Stochastic cost frontier, subsidies, heteroscedasticity, local public bus transportation, cost efficiency, panel data

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[a] Corresponding author: Maria Nieswand, DIW Berlin Graduate Center, Mohrenstrasse 58, D-10117 Berlin, Germany. tel.: +49-(0)30-89789-224, fax.: +49-(0)30-89789-104; mnieswand@diw.de.

[b] Matthias Walter, Dresden University of Technology, Chair of Energy Economics and Public Sector Management.

1 Introduction

Currently, Germany's local public transit sector in total receives about 13 billion Euros of public financing per year.[1] The funding is distributed in ample and sometimes parallel ways which might offer even contrary incentives for the recipients (Umweltbundesamt 2003a). To evaluate the subsidies' effect on the performance of operators can help identify improvements of the subsidies' guiding function and make appropriate recommendations on potential reductions in funding. In general, subsidies are considered crucial for a suitable provision of public transit that is an important component of population mobility. Hereby, the bus sector is of particular interest since it supplies more than two-thirds of the demand for general local public transportation[2] and it is notably employed in rural areas (VDV 2009a). The reality that bus transit demand in non-urban areas is twice that in cities demonstrates the necessity of publicly providing mobility services, particularly in less densely populated areas. Several hundred bus companies which are predominantly publicly owned serve the market and constitute local and temporary monopolies.

Even though the average degree of cost coverage of the German public transit sector grew over the past decade (VDV 2009b), it is commonly assumed that most local public transit is unprofitable[3] and therefore depends heavily on public financial support. Historically, the most significant reason for the sector's fiscal deficit originates in the explosive growth of private vehicle usage during the second half of the twentieth century (Goeverden et al. 2006). In response, Germany established a complex financing system whereby all governmental units, i.e. the federal government, federal states, and lower-level government bodies, act as financiers. The individual financing instruments can be roughly divided into investment-related and non-investment-related groups (Umweltbundesamt 2003b). The first group concerns investments in infrastructure and vehicles, while the second group can be subdivided further into: i) grants for operating costs, ii) compensation for target group-related traffic, iii) tax reductions and other benefits, and iv) deficit balancing (Umweltbundesamt 2003a). The annual level of subsidies is partially determined by the profitability of the operators and some types might affect the performance of companies negatively.

This paper focuses on deficit balancing, which we theorize can be influenced by firm management. We investigate the impact of this subsidy type on the performance of local bus companies by conducting a parametric form of efficiency analysis. To account for the

[1] The largest proportion of this amount is dedicated to infrastructure-intensive and rural public transport provided with light trains.
[2] General local public transit refers to modes including buses, trams, light railway and metros. It is particularly distinguished from rail-bound local public traffic provided with light trains. All modes together build the local public transit in total.
[3] That is, overall costs exceed the revenues from fares.

character of deficit balancing in our econometric analysis, we link them directly to the cost inefficiency distribution. To our knowledge, this approach has not been pursued in the literature on public bus operations, and we believe it promises to broaden our understanding about subsidizing the sector.

The deficits that occur when revenues from ordinary activities become negative can be addressed by various accounting treatments, e.g., loss forwarding or loss absorption.[4] Loss absorption can be characterized as an internal payment raised by the owners (shareholders) of a bus company to equalize the annual deficit that is not balanced by amounts from retained earnings. These additional payments differ from other types of subsidies because they depend on the extent and treatment of the losses reported by a company. In other words, the payments are *firm-influenced*. Vickery (1980) outlines three rationales to justify subsidies to local transit. First, because transit operates under conditions of substantial economies of scale,[5] marginal costs are lower than average costs, and under-pricing average costs, e.g., for social reasons, produces a gap in cost coverage. Second, competing modes of transit receive substantial subsidies. Third, special requirements for the underprivileged or disabled, e.g., an inability to use alternate forms of transportation, justify public financial support. Essentially, Vickery states the conclusions later reached by Karlaftis and McCarthy (1998), who note that with the exception of the economies of scale rationale, public transit subsidies are based upon non-economic arguments, i.e. social objectives. In addition, public subsidies are a second-best instrument to address the urban externalities such as noise, congestion and pollution, in order to shift demand from private to public transportation (Button 1993). However, a large body of literature provides empirical evidence for cost-increasing effects of subsidies in public transit (for a review, see e.g., Karlaftis and McCarthy 1998). Thus, financial support might extend the failure to cover costs instead of compensating for exogenously caused cost increases.

The literature analyzing cost structure and performance of public bus transportation dates to the 1950s and divides into the two strands: regression analysis and frontier analysis.[6] Early work, including Johnston (1956), Miller (1970), Viton (1981), and Berechman and Guiliano (1985), are chiefly concerned with establishing concepts of cost models and cost functions' properties within the context of public bus transportation,[7] but also with appropriate regression estimation techniques. The regression analyses concerning subsidies highlight further aspects of public transportation, e.g., fares, unit costs, and demand. Bly et al. (1980) and Bly and Oldfield (1986) find reduced effects on fares and increased effects on

[4] The German transport accounting standards denote these payments as "Verlustübernahme durch Eigentümer".
[5] This has also been shown in a variety of empirical studies, among them Cambini et al. (2007) and Farsi et al. (2006).
[6] Piacenza (2001) surveys theoretical and empirical issues associated with both approaches.
[7] See Berechman (1993) for a general survey of public transport.

demand as well as increased unit costs and reduced labor productivity because of subsidies. The data they use comprises multiple countries, and therefore the findings appear to reflect general trends. Pickrell (1985) examines the relationship between deficits and subsidies in the US transit sector and concludes that government subsidy programs would be more effective if transit operators could gain a measure of control over operating costs, adapt their services to changes in demand, and reconstruct fares to recognize the variations in supply costs. In addition, Pickrell proposes that a revision of the subsidy mechanism could also contribute to improving the situation. Thereby, a major effort in revising state and federal programs is re-establishing incentives for operators. The success of subsidies appears to be closely related to the level of government awarding the financial support. Anderson (1983), Pucher (1988), and Filippini et al. (1992) find that subsidies by low-level government bodies cause fewer cost increases than subsidies funded by high-level government bodies. In other words, the impacts of subsidies on costs are less harmful when close relationships exist between funding bodies and companies.

During the early 1980s, performance measurement using frontier analysis entered the discussion (for a review, see e.g., De Borger et al. 2002 and De Borger and Kerstens 2008). Based on the idea of Farrell (1957), frontier methods determine the best practice behavior in an industry (or a sample) and estimate the unit-specific degree of inefficiency relative to the best-practice benchmark. Frontier approaches mainly estimate the efficient frontier either by nonparametric linear programming, or by parametric techniques which assume a functional form representing the underlying input-output-transformation. The advantages of parametric efficiency analysis are its accountability for statistical noise, applications to panel data, and incorporation of the time horizon. This paper applies stochastic frontier analysis (SFA), a widely used parametric technique which yields estimation residuals that are interpreted as measures of inefficiency. Even though there is continued interest in performance measurement focusing on public bus operators, the empirical evidence on subsidies derived from frontier analysis is limited. In a nonparametric analysis, Obeng (1994) investigates the technical efficiency of 73 US single mode bus systems in 1988 by comparing the efficiency scores from a base model to its re-estimation including subsidies (measured as total operating and capital subsidies from all sources) as an additional variable. He finds higher technical efficiencies when subsidies are considered. However, it is unclear whether Obeng's results are truly subsidy-related, or are driven by the curse of dimensionality.[8] Kerstens (1996) uses

[8] The curse of dimensionality is a well-known phenomenon in Data Envelopment Analysis; it is the overestimation of efficiency when the number of variables is high relative to the number of observations. For theoretical considerations see Simar and Wilson (2008) and Adler and Yazemsky (2009); for an empirical investigation see e.g., Nieswand et al. (2010).

nonparametric technology references to evaluate the technical efficiency of 116 French bus operators in 1990. Conducting a Tobit regression in a second stage, the author shows that subsidies (measured as the share of subsidies in total operating costs) subvert technical efficiency. Filippini et al. (1992) estimate the cost efficiency of a panel of 62 Swiss bus operators in 1988 by displaced ordinary least squares (DOLS). The subsequent ordinary least square (OLS) regression reveals that cost efficiency is positively influenced by the low-level government share in deficit subsidies and the amount of compensatory payments. Sakano and Obeng (1995) examine the technical and allocative efficiency of 134 US single mode bus firms in 1988 using a stochastic frontier approach developed by Schmidt and Lovell (1979, 1980). Using OLS regression, they find that firm size rather than operating and capital subsidies affects the allocative efficiency between labor and capital. Sakano et al. (1997) extend Sakano and Obeng (1995) by incorporating the operating and capital subsidies in the cost minimization problem such that firms minimize costs net of subsidies subject to the production function constraints. This specification allows them to distinguish allocative inefficiency due to subsidies, or to internal factors. They pool data on US urban bus companies from 1983 to 1992 and find that allocative inefficiency mainly originates in factors internal to the firms, not the subsidies. Further, Sakano et al. indicate that subsidies cause notable deviations from optimal input factor proportions, i.e. the excess use of labor relative to capital and the excess use of fuel relative to capital and labor.

Unlike previous research, we directly incorporate the firm-influenced subsidy as a heteroscedastic variable in the standard deviation of inefficiency term, i.e. the half-normal error term. This approach is proposed by Bhattacharyya et al. (1995) and Hadri et al. (2003) who suggest among others, to assign factors which are under the control of firms (managerial determinants) to the inefficiency term.[9] This aligns with Kerstens (1996) who notes that subsidies influence efficiency, but not the transformation of inputs to outputs. Our approach accounts for endogeneity of inefficiency and deficit-balancing subsidies, enabling us to capture a potential bias due to heteroscedasticity possibly related to firm size. The widespread belief that larger firms have a higher facility of decision-making is relevant to our approach for two reasons. First, German bus companies offer a wide range of characteristics and thus, firm size. Second, Caudill et al. (1995) argue that especially the residuals in frontier estimation are sensitive to heteroscedasticity, because the frontier changes when the error

[9] The association of factors under the control of firms (managerial determinants) and inefficiency is particularly distinguished from exogenous factors that are instead associated with the noise term.

dispersion increases.[10] This sensitivity is likely to carry over to the inefficiency measures and therefore must be considered.[11]

This paper contributes to the existing literature by investigating a sample of German local public bus operators and applying recent panel data model specifications of SFA that account for unobserved heterogeneity and provide time-varying and firm-specific efficiency estimates. Moreover, to allow for variations in the optimal (reference) production technology, one of our two model specifications relaxes the strong assumption of equal output and price parameters by randomizing them.

The remainder of the paper is structured as follows. Section 2 discusses the applied methodology and introduces the model specifications and data. Section 3 shows the results of our regressions and discusses in depth our analysis of firm-specific cost efficiencies. Conclusions and suggestions for policy-makers are given in Section 4.

2 Methodology and data

2.1 Cost function

Public transit can be considered a production process whereby inputs, e.g., labor and capital, are transformed into one or multiple outputs, e.g., seat-kilometers. The production process is well-known by now and the corresponding cost function of public bus operators has been discussed at length. Kumbhakar (1997) notes that independent from the output produced, it is important to use inputs in order to minimize the cost of producing a given level of output. Cost-minimizing behavior is required when a cost function is applied (Coelli et al. 2005). Further, output quantities are predetermined by public (government) entities that make decisions about the public transport services to be supplied. Therefore, we apply an input-oriented approach and the total cost function can be written as

$$C = f(Y, p_L, p_K, di, D_{east}, t) \tag{1}$$

[10] In regression estimation this is a minor problem, because average cost functions are usually estimated by least squares and estimators based on means are no longer efficient but still unbiased when symmetric error dispersion is present (Caudill et al., 1995).

[11] Using a Monte Carlo study for the estimation of a cross-sectional cost frontier of banking institutions, Caudill et al. (1995) find overestimation of inefficiency for small firms and underestimation of inefficiency for large firms when heteroscedasticity is ignored.

where total costs (C) depend on the level of output (y), two input factor prices for labor (p_L) and capital (p_K), and structural variables that are beyond the control of companies. These structural variables are the density index (di) and a dummy variable (D_{east}), which realizes the value of one if a company operates in one of the newly formed German states. A linear time trend (t) captures a neutral technological change.

Concerning the functional form we opt for a flexible form, i.e. the translog cost function.[12] We choose the mean to be the local point around which the function is approximated. Hence, the variables for output, factor prices, and density index are divided by their respective mean. This transformation allows interpreting the estimated coefficients as elasticities. After imposing linear homogeneity of costs in input prices of degree one by dividing cost-related measures by the input factor price for labor, the translog cost function is

$$
\begin{aligned}
\ln\left(\frac{C_{it}}{p_{L_{it}}}\right) = \ln C_{it}^* &= \alpha_0 + \beta_Y \ln Y_{it} + \beta_{p_K} \ln\left(\frac{p_{K_{it}}}{p_{L_{it}}}\right) \\
&+ \frac{1}{2}\left(\beta_{YY}\left(\ln Y_{it}\right)^2 + \beta_{p_K p_K}\left(\ln\left(\frac{p_{K_{it}}}{p_{L_{it}}}\right)\right)^2\right) \\
&+ \beta_{Yp_K} \ln Y_{it} \ln\left(\frac{p_{K_{it}}}{p_{L_{it}}}\right) + \beta_{di} \ln di_{it} + \beta_{D_{east}} D_{east} + t
\end{aligned}
\tag{2}
$$

where α_0 represents the intercept, and all other $\beta's$ represents the variables' coefficients to be estimated. The indices i and t indicate the unbalanced panel structure of our data where $i = 1,2,...,33$ denote the companies, and $t = 1,2,...,12$ the time period of the specific observation.

2.2 Econometric model

To estimate the translog cost function we employ stochastic frontier models for panel data. The advantage of using panel data models is that they allow accounting for both unobserved heterogeneity between firms and dynamics. The first panel data models for SFA were proposed by Pitt and Lee (1981) and Schmidt and Sickles (1984). Both models allow for firm-specific inefficiency estimation but regard only time-invariant inefficiency. Thus, they are no longer considered here. Numerous approaches include time-varying inefficiency, such as

[12] For previous applications, see e.g., Bhattacharyya et al. (1995); Farsi et al. (2006), Filippini and Prioni (2003).

Kumbhakar (1990) and Battese and Coelli (1992, 1995). This paper uses the true random effects (TRE) model proposed by Greene (2005), who extends conventional models by including an additional random intercept which captures unobserved heterogeneity. This model can be illustrated as

$$\ln\left(C_{it}^{*}\right) = \alpha_0 + \alpha_i + x'_{it}\beta + v_{it} + u_{it} \tag{3}$$

with C^* depicting the transformed cost variable and $x'\beta$ collecting the explanatory variables and the respective parameters. α_0 is a common intercept and $\alpha_i \sim iid\ N\left(0,\sigma_\alpha^2\right)$ a firm-specific random intercept which captures unobserved time-invariant heterogeneity. Noise is captured by a two-sided error term, $v_{it} \sim iid\ N\left(0,\sigma_v^2\right)$, while $u_{it} \sim iid\ N^+\left(0,\sigma_u^2\right)$ denotes a one-sided, non-negative random variable which represents the firm-specific inefficiency. Since we wish to include a managerial determinant as heteroscedastic variable z in the inefficiency function, we parameterize the standard deviation of the one-sided inefficiency term such that $\sigma_{u_{it}} = \exp(\delta' z_{it})$ after Bhattacharyya et al. (1995). z collects an intercept (z_0) and the heteroscedastic variable which represents our measure of deficit-balancing subsidies (z_1). This variable is standard deviation corrected to improve the estimation. δ denotes the vector of coefficients to be estimated in the heteroscedastically specified inefficiency function. Introducing heteroscedasticity in the half-normal model implies an individual-varying mean of the inefficiency since $E[u_i] = \sigma_{u,i}\,\phi(0)/\Phi(0) = 0.79788\sigma_{u,i}$ where ϕ denotes the probability density function of the inefficiency function of the normal distribution and Φ is its cumulative distribution function (Greene 2007).

Several extensions of heteroscedastic models have been proposed: Hadri (1999) introduces double heteroscedasticity (heteroscedasticity in both the one-sided and the two-sided error terms) for cost frontiers; Hadri et al. (2003) extend this approach to the cases of production frontiers and panel data. We concentrate only on the heteroscedasticity of the one-sided error term. According to Kumbhakar (1997), from an economic view, it makes more sense to model heterogeneity in the variances of firm-specific components, especially when there are unobserved firm-specific components.

The TRE model assumes that the explanatory variables are uncorrelated with the firm-specific effect. Farsi et al. (2005) point out that at least time-variant efficiency measures are not very sensitive to such correlations because the correlations may be captured by the coefficients of the cost function and do not affect residuals. The TRE model is a special case of the random parameters (RP) model which additionally allows other coefficients to be randomized. We let the coefficients of output (β_Y) and the price ratio (β_{p_K}) vary between companies. Hence, the frontier estimated by this RP model does not assume the same optimal technology for every firm. Justifications for assuming a different technology may origin first, in different bus types, e.g., diesel versus hybrid, or low floor versus conventional, and second, in different optimal input factor ratios according to a company's environment. The heteroscedastic formulation of the inefficiency term and all other assumptions are the same as before.

2.3 Data

The dataset incorporates an unbalanced panel of 33 bus operators in urban and rural areas. The time period covers twelve years (1997-2008) for a total of 231 observations. The panel structure is such that 50% of the companies are observed seven years or less, and 25% are observed ten years or more. Table 1 presents the data characteristics. The data derive from multiple sources, i.e. the physical data (e.g., seat-kilometers) is from the annual statistics of the German Association of Transportation Companies (VDV), and the monetary data (e.g., personnel expenditures, loss absorption) is from the balance sheets published in annual reports and the Federal Gazette (Bundesanzeiger).

Table 1: Descriptive Statistics

Variable	Mean	Median	Std.Dev.	Min	Max
Total costs (Y) [m Euro] [a]	39.47	33.47	24.22	3.82	95.04
Seat-kilometers (skm) [m km]	750	719	423	55	1,870
Labor price (p_L) [Euro/ FTE] [a]	46,896	46,689	11,566	10,693	86,243
Capital price (p_K) [Euro/seat] [a]	1,360	1,237	590	568	3,517
Density index (di) [head/ km] [b]	412	344	333	61	2460
Dummy East (D_{east}) [c]	0.26	0.00	0.44	0.00	1.00
Subsidy ratio (z_1) [a, d]	0.14	0.14	0.14	0.00	0.55
N = 33, T = 12, observation = 231					

Note: [a] Base year 2008 [b] Population in operating area per network length [c] East = 1: Company operates in Eastern Federal States (59 observations), East = 0: Company operates in Western Federal States (172 observations) [d] Loss absorption in Euro/ total costs in Euro

Total costs (Y) include personnel expenditures, material costs, other operating expenses, depreciation, interest on borrowed capital,[13] and opportunity costs of equity. The latter is measured by multiplying the individual equity base of each observation with the corresponding interest rates of corporate bonds (Deutsche Bank, 2010) plus a 2% risk premium. We note that this approach treats the companies equally and is justified by the fact that our dataset includes operators that are predominantly publicly owned. Only five companies[14] have a mixed ownership structure (public and private), and none are purely privately owned. Dividing personnel expenditures by the number of full-time equivalents (FTE) provides the input factor price for labor (p_L). To approximate capital costs we use the residue from subtracting personnel expenditures from total costs, and thus consider all non-labor costs as capital costs. This approach is frequently used when companies do not report capital costs directly or it is not possible to apply the capital inventory method (e.g., Farsi et al. 2006; Filippini and Prioni 2003). We then calculate the input factor price for capital (p_K) as the ratio of capital costs to the number of seats.[15] Seats are our preferred unit measurement, because unlike the number of buses, the number of seats accounts for different bus sizes. Both input factor prices vary notably. Walter (2010) argues that labor and capital cost shares are significantly related to outsourcing, because outsourcing moves internal labor costs into purchased services which are part of material costs. The large variation in labor prices furthermore depicts the interregional wage differentials, particularly for the distinction between wage levels in Eastern and Western parts of the country.[16] The differences in capital prices seem to be due to rural and non-rural characteristics of the operating environments.[17] The capital price is lower for rural operating areas where companies tend to employ older buses with less comfort devices. Cost reductions due to lower depreciation costs appear to outweigh the higher maintenance costs associated with old buses. All cost data is inflation-adjusted to 2008 using the German producer price index (Destatis 2009).

Seat-kilometers (skm) are the supply-oriented measurement of outputs. De Borger and Kerstens (2008) note that objectives and heterogeneity of public bus transit imply that both supply- and demand-oriented approaches are relevant. We use the former approach since local

[13] We use the account “interest paid and similar costs” reported in the financial reports.
[14] These companies are ASEAG in Aachen, KVG in Kiel, KVG in Koblenz, KVS in Saarlouis, and KVIP in Uetersen.
[15] The number of seats is calculated by the number of seat-kilometers multiplied by the number of buses divided by the number of vehicle-kilometers. This approach assumes a similar deployment of all buses in the fleet, which should be the usual case.
[16] The average labor factor price is 50,616 Euro/FTE in the old West German States, and 36,050 Euro/FTE in the newly formed German States.
[17] The average capital price is 1,133 Euro/seat in rural and 1,563 Euro/seat in non-rural operating areas, respectively.

public transport is a public service obligation with pre-determined service levels which, and at least in the short-run, are not open to companies' influence.

For comparability between operators, we use a density index (di) capturing the network characteristics beyond firm's control. We define di as the ratio of population living in the operating area over the kilometers of network length gathering e.g., differences in the service accessibility for customers, in speed, and in network complexity. A dummy variable (D_{east}) addresses the cost differences between companies operating either in newly formed (D_{east} equals 1) or in old West German States. A substantial restructuring of public transport in the newly formed German States, supported by state aid, followed Germany's reunification and hence affects cost structures.

To determine the firm-influenced subsidies, we use the amount of loss absorption directly paid by the firm owners (shareholders) to balance negative revenues from ordinary activities. Deficits can also be recovered by depleting accumulated retained earnings, carrying forward a loss, appropriating reserves, etc., all of which depict a firm's ability to handle losses without demanding additional money.[18] Such accounting treatments support the assumption of firm-influence on loss absorption. We assume that the amount of required loss absorption is assessable by firm's management, since exogenous cost disadvantages are addressed by other subsidies mentioned in Section 1. The subsidy ratio (z_1) is then constructed by the ratio of loss absorption over total costs.

3 Empirical evidence and interpretation

3.1 Regression results

Table 2 provides the regression results for the TRE and the RP models.[19] The obtained results are robust and show significant coefficients with small standard errors.

The first order coefficients, β_Y and β_{p_K}, have the expected, positive signs and are statistically significant at the 1% level. Given that all variables of the cost function are in logarithmic form, we can interpret the estimates as cost elasticities. The TRE model shows an output cost elasticity of 0.457 for the mean company, indicating an under-proportional increase of costs when output enlarges. With the same implication of existing economies of

[18] We make only one exemption from this treatment and consider the appropriation of reserves as loss absorption if shareholders obviously add the amount of the pending loss to the reserves. In this case only the accounting practice differs, but these accounts mirror the behavior we are studying.

[19] We conduct the estimation with Limdep 9.0 using 1,000 Halton draws for each model.

scale, β_Y is substantially higher in the RP model (0.622) and exhibits a significant standard deviation of 0.263. Farsi et al. (2007) refer to output coefficients as the marginal costs of transportation systems and conclude that marginal costs are highest for tramway systems, followed by trolley-bus and motor-bus systems. The authors explain this particular order by the transportation systems' respective intensities of labor and capital costs. Based on the significant standard deviation, our results further indicate that marginal costs variations are also present within the same transportation system, i.e. motor-buses. These differences might be due to differences between urban and rural operating systems.

Table 2: Regression Results

		TRE Model		RP Model	
Variable		Coefficient	Std.Dev.	Coefficient	Std.Dev.
Parameters of the cost function					
Constant	α_i	-7.042 ***	0.014	-6.970 ***	0.011
Std.dev. of α_i	σ_α	0.246 ***	0.009	0.190 ***	0.006
Output (Seat-km)	β_Y	0.457 ***	0.019	0.622 ***	0.013
Std.dev. of output	σ_y			0.263 ***	0.009
Capital price	β_{pK}	0.413 ***	0.012	0.415 ***	0.011
Std.dev. of prices	σ_{pK}			0.320 ***	0.013
Output^2	β_{YY}	-0.363 ***	0.020	-0.215 ***	0.015
Capital price^2	β_{pKpK}	0.074 ***	0.019	-0.066 ***	0.023
Output * Capital price	β_{YpK}	-0.285 ***	0.021	-0.185 ***	0.018
Density index	β_{di}	0.042 ***	0.007	0.024 ***	0.006
Dummy east	β_{Deast}	-0.235 ***	0.015	-0.238 ***	0.014
Linear time	β_t	-0.006 ***	0.001	-0.011 ***	0.001
Parameters of the inefficiency function					
Constant of σ_u	δ_0	-4.348 *	2.223	-4.567 ***	1.675
Subsidies ratio	δ_{z1}	1.681 **	0.799	1.906 ***	0.625
Std.dev. of v	σ_v	0.066 ***	0.002	0.043 ***	0.001
Lambda	σ_u/σ_v	0.326		0.483	
Wald test H_0: $\delta_0=\delta_{z1}=0$		5.533 (p-value = 0.063)		13.879 (p-value = 0.001)	
Loglikelihood function		218		263	

Note: *** indicates a significance level of 1%, ** indicates a significance level of 5%, and * indicates a significance level of 10%.

The capital price coefficients are similar across models (0.413 and 0.415). However, the randomized capital price coefficient in the RP model has a large standard deviation of 0.320. Since the price coefficient can be interpreted as the optimal cost share of the individual input factor, σ_{p_K} indicates an optimal input mix that varies across companies. This is likely to be related to firm size and emphasizes the necessity to account for different production structures and operating frameworks.[20] Moreover, varying prices and marginal costs can be explained by the diversity of input virtues, i.e. regarding capital diversity, De Borger and Kerstens (2008) mention that bus fleets are heterogeneous in terms of vintages therefore lead to diverse depreciation patterns. They also mention that different fuel power technologies are applied. Even though hybrid power technologies might not have an important impact over the sample period, low-floor technologies, quality improving devices, e.g., air conditioning, and different types of buses, e.g., standard and articulated buses, are relevant. While hybrid technologies might not have important impacts during our sample period, we note that low-floor technologies, quality improvements, e.g., air conditioning, etc. are relevant.

The second order coefficients, β_{YY}, $\beta_{p_K p_K}$, and the interaction coefficients, β_{Yp_K}, are statistically significant but do not always show the expected negative sign. The positive coefficient $\beta_{p_K p_K}$ in the TRE model violates the concavity property of cost functions in input prices and suggests a non-cost-minimizing behavior of firms in response to changes in prices. The same result found in other regulated industries, see e.g., Karlaftis and McCarthy (2002), Farsi et al. (2005), and Farsi and Filippini (2009), is explained by the considerable barriers of cost-minimizing strategies.[21] Plausibly, these constraints could also apply to the German public local bus transport as a highly state-influenced sector. However, the more flexible technology shows a negative sign of the second-order coefficient $\beta_{p_K p_K}$ and thus, the RP model satisfies the theoretical requirements of cost functions. Applying the Wald test we cannot confirm the hypothesis of Cobb-Douglas-typed technologies at the 1% level.[22]

For the coefficients of the structural variables, β_{di} and β_{Deast}, both models show consistent implications of the estimates. Commonly, urban transportation systems are characterized by lower average speeds and higher network complexity which explains the positive sign of the density index coefficient β_{di}. In addition, the coefficient contains some costs associated with network length, e.g., costs for bus stops. Thus, operating areas with a higher population density yield higher costs. The dummy variable's coefficient β_{Deast} implies lower costs for companies operating in eastern Germany. Apparently, restructuring after German reunification shows a significant cost-reducing impact. The expected negative coefficient value of the linear time is small (0.006 and 0.011) which implies only minor technological advances associated with cost reductions. De Borger and Kerstens (2008)

[20] The mean share of capital costs in total costs is 55.1% with a standard deviation of 12.6%.
[21] For example, input prices that are constrained by regulation and a less-distinctive sensitivity to price changes in public sectors can be considered barriers.
[22] The test statistics take value of 481 (TRE model) and 217 (RP model) which clearly exceed the critical value of 12.84 at the 0.5% significance level.

explain the small time trend with the established technology of bus driving, increasing congestion levels impeding performance improvements, and improvements in technical efficiency rather than technological progress.

The focus of this paper is on the heteroscedastic variable, i.e. on the effect of the subsidy ratio on the cost inefficiency's variance. The two models reveal positive and statistically significant coefficients for the subsidy ratio. δ_{z_1} is 1.681 in the TRE model and 1.906 in the RP model which implies an increasing standard deviation in cost inefficiencies for larger z_1. Conducting a Wald test on the heteroscedasticity of the inefficiency's standard deviation fails to confirm the hypothesis of zero values for δ_0 and δ_{z_1} at the 10% significance level in the TRE model and at the 1% level in the RP model. Since efficiency is half-normally distributed, the distribution's probability function flattens with increasing z_1 and the probability mass shifts towards the tail. Therefore, we conclude that the performance range increases when the proportion of subsidies to total costs increases.

3.2 Cost Efficiencies

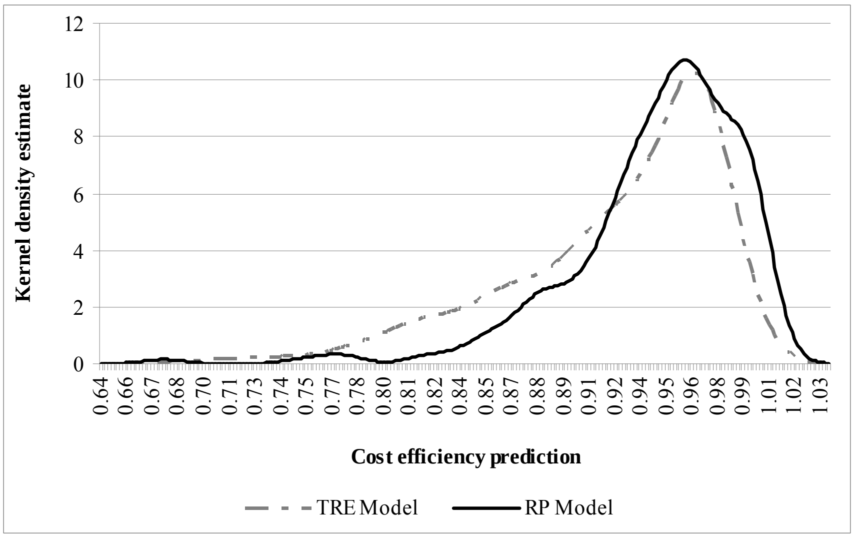
Table 3 shows the characteristics of the predicted cost efficiencies. For the 231 observations considered, the econometric models show an overall mean cost efficiency of 92% and 93% in the TRE model and RP model, respectively. The minimum value of cost efficiency is 69% in the TRE model and 66% in the RP model while the highest is close to 99% in both.

Table 3: Cost Efficiency Predictions

Model	Mean	Median	Std.Dev.	Min	25% quantile	75% quantile	Max
TRE Model	92.14%	93.98%	5.82%	69.08%	89.34%	96.66%	98.86%
RP Model	92.80%	93.68%	4.75%	65.99%	90.98%	96.07%	98.73%

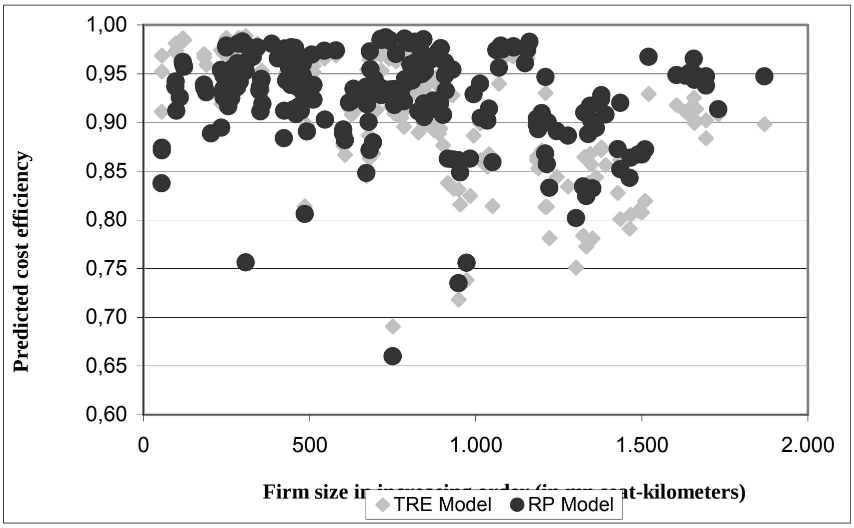
Figure 1 depicts the distribution of the cost efficiency predictions. Both curves support our assumed half-normal distribution of efficiency and so we conclude that the underlying models are appropriate for the given data. However, the probability mass in the RP model is closer to the efficient tail of the distribution representing the model's characteristic of allowing more heterogeneity between companies without attributing the cost differences to inefficiency.

Figure 1: Kernel Density of Cost Efficiency Predictions



A detailed look at firm-specific efficiency estimates with respect to firm size in Figure 2 reveals that larger firms especially benefit from the RP model with a more flexible underlying technology. This has two implications. First, there is no clear indication for size-related differences in performance between smaller and larger local public bus operators. Second, the TRE model appears to miss important information on the technology characteristics.

Figure 2: Cost Efficiency and Firm Size



Since we are interested to find whether less-subsidized operators perform better, we conduct a Welch test which compares the mean cost efficiency of two groups while allowing for any underlying distribution of the standard deviation.

We divide the companies in two groups according to the subsidy ratio z_1; group 1 comprises all observations recording zero deficit balancing (95 observations) and group 2 comprises all others (136 observations). The test first calculates the mean cost efficiency of all group members for each group and then tests whether the means differ significantly from each other. The obtained test results are illustrated by Table 4.

Table 4: Welch Test on Group Mean Cost Efficiency

		TRE Model		RP Model	
	Group size	Mean	Std.Dev.	Mean	Std.Dev.
Overall mean efficiency	231	92.14%	5.82%	92.80%	4.75%
Mean cost efficiency for group 1*	95	93.22%	0.50%	94.23%	3.69%
Mean cost efficiency for group 2**	136	91.39%	0.54%	91.81%	0.44%
t-value		2.484		4.171	
p-value		0.014		0.000	

Note: * indicates that the subsidy ratio z_1 equals zero. ** indicates that the subsidy ratio z_1 is greater than zero.

Both models consistently show that group 1 performs better in terms of cost efficiency. Those companies with a subsidy ratio of zero achieve a mean cost efficiency of 93.22% and 94.23% in the TRE model and the RP model, respectively, while companies with a positive subsidy ratio achieve mean cost efficiencies of 91.39% (TRE model) and 91.81% (RP model). We cannot confirm the null hypothesis of non-differing mean cost efficiency values, since the respective average values are different at the 5% (TRE model) and at the 1% significance levels (RP model). From this we conclude that operators demanding no subsidies in the form of loss absorption, on average, perform better. This coincides with De Borger and Kerstens (2008) who, conclude from their empirical evidence that subsidies have cost-increasing and performance-worsening effects. Our results extend the empirical evidence of efficiency-decreasing effects to subsidies which are firm-influenced, target-unspecific, and unlimited.

4 Conclusion

Subsidies are commonly allocated to public bus transportation to compensate exogenously caused cost increases. However, the empirical evidence implies reversing effects of financial supports on costs, i.e. cost increases due to subsidies. Interest in curtailing Germany's generous public budgets and previous empirical findings spurred our examination of the effect of subsidies on operator performance. We considered loss absorption, i.e. a payment by a firm's owner to balance negative revenues from ordinary activities, as firm-influenced subsidies for two reasons. First, a wide range of subsidies exists to compensate for exogenously caused cost disadvantages, and second, losses can be balanced via different accounting treatments. We hypothesized that bus operators with higher subsidies would perform worse and thus exhibit reduced cost efficiencies. Using a heteroscedastic stochastic frontier cost function, we analyzed an unbalanced panel of 33 bus companies observed over a time period of twelve years for a total of 231 observations. To estimate the translog cost function, we used two stochastic cost frontier models (true random parameter model and random parameter model) which differ in their ability to allow for varying optimal cost structures among companies. The random parameter model is preferable to the true random parameter model in three respects: first, it achieves a higher loglikelihood function; second, it satisfies the concavity property of the cost function; and third, it shows significant standard deviation coefficients for output and prices. To ignoring the latter leaves important information unexploited. The finding of a positive effect of subsidies on the standard deviation of cost inefficiency showed that inefficiency is not equally distributed across subsidy levels. Relative to total costs, the larger the subsidies the wider the range of companies' efficiency. We also found that German bus companies are more cost efficient when they have lower ratios of subsidies to total costs.

We suggest that our findings imply that subsidies which are partially under control of firms can function as a regulatory tool to decrease subsidies and therefore public budgets. The dilemma, of course, is that publicly owned companies often run deficits which must be balanced by their owners – local public transport companies tend to fare the worst in this regard, because they are stuck in deficits. One option for municipalities is given by Berlin, which now negotiates contracts that predefine the deficit payments and bind them to key performance indicators for the life of the contract. A further option would be to incentivize payment for managers more intense in order to give them a natural reason of cost efficiency compliance. Finally, noting a higher awareness of profitability in private companies, a stronger involvement of the private sector appears favorable. Hence, the German federal government should continue to encourage competitive tendering in local bus transport.

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